I. StromSight : A Deep Learning Based Cyclone Intensity Estimation Using INSAT-3D IR Imagery

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***Abstract*— Cyclone intensity estimation underpins effective disaster management in coastal regions. This study presents a novel deep learning approach using INSAT-3D infrared (IR) images to improve the accuracy and timeliness of this critical task. A convolutional neural network (CNN) is trained on a vast dataset of INSAT-3D IR footage and corresponding ground truth data (cyclone classification, pressure, wind speed, cloud patterns). The model addresses key challenges like dynamic cyclone systems and multi-parameter prediction using a multi-task learning architecture. Rigorous evaluation demonstrates strong correlations between predicted and observed intensity, revealing the model's effectiveness in accurately assessing cyclone strength. This paves the way for enhanced disaster preparedness and response in vulnerable coastal communities facing the increasing threat of these powerful storms.**

Keywords— Cyclone intensity, Cyclone Direction, Deep learning, INSAT-3D, convolutional neural network, multi-task learning, disaster management, coastal communities, INSAT-3D IR Imagery, Data

I. Introduction

The destructive force of Cyclones, also known as hurricanes or typhoons in different regions of the world, are among nature's most powerful and unpredictable forces. These large, spinning storm systems, powered by warm ocean waters and meteorological conditions, can cause widespread devastation when they make landfall, posing a severe threat to coastal regions. Cyclone strength, a crucial predictor of the potential for destruction and loss of life, must be precisely and quickly predicted to enable effective disaster management, preparedness, and early reaction. This estimation has historically relied on a combination of meteorological measurements, numerical weather models, and satellite photography. However, with the introduction of deep learning algorithms, which have proven to be excellent tools for improving the accuracy and efficiency of cyclone intensity estimation, the field of meteorology has undergone a dramatic shift in recent years. This study dives into the promising field of deep learning to create a cutting-edge method for estimating cyclone intensity. We specifically use the capabilities of the Indian National Satellite System-3D (INSAT-3D), which has advanced imaging resources such as a high-resolution thermal infrared (IR) channel. INSAT-3D IR imaging provides a unique and valuable viewpoint for tracking, monitoring, and analysing cyclones, making it a perfect data source for our novel technique. Cyclone intensity is generally graded from Category 1 (weakest) to Category 5 (strongest) using the Saffir-Simpson Hurricane Wind Scale or the Dvorak approach. Central pressure, maximum sustained wind speed, and cloud patterns all contribute to the intensity. Estimating these factors accurately and on time is critical for making educated decisions about evacuation, resource allocation, and disaster response. Traditional methods, on the other hand, frequently encounter difficulties, particularly when dealing with fast forming cyclones, intricate cloud formations, and restricted data availability. Deep learning, a type of machine learning, has demonstrated extraordinary ability in solving complicated and data-rich tasks.

Convolutional neural networks (CNNs), a type of deep learning model specifically intended for image analysis, offer a viable approach for improving cyclone intensity estimation. CNNs excel in automatically learning and extracting relevant features from images, which is especially useful in the case of INSAT-3D IR imagery. Based on well-established meteorological parameters, these attributes are then used to forecast cyclone intensity. The centre of our research is the creation of a deep learning model trained on a large dataset of INSAT-3D IR pictures. This dataset spans cyclones of varied strengths and is rigorously annotated with ground truth data, providing the necessary foundation for the model's training and evaluation. Furthermore, our model handles the intrinsic complexity of cyclone intensity estimation by using a multi-task learning strategy. This method allows the model to estimate both central pressure and maximum sustained wind speed, providing a more complete picture of cyclone severity

II. Literature Survey

In Preparation for our work, we conducted a thorough review of relevant literature to ensure the accuracy of our results.The papers we studied are presented in this section as a Literature review. Upon reviewing these papers, it became evident that numerous researchers have introduced a variety of authentic models for intensity estimation.. Researchers have established innovative techniques for the proper estimation of cyclone intensity , and a summary of their work is included in this section.

In their 2019 paper, Wimmers and colleagues experimented with the feasibility of using deep learning using the convolutional neural network model called DeepMicroNet to determine the intensity of TCs based on the data taken from satellite observations, among others. The focus of their works was on determining whether such innovative teaching apps can be applied in meteorology and pinpointing the room for development of these apps.The results of the model achieved satisfactory accuracy marked by a factor of 14 kt of root-mean-square error (RMSE), however, it presented certain limitations in the manner of correctly predicting the intensity of category 5 TCs because of its lack of a well-training dataset.This work conveys the strong optimism of deep learning in the meteorology discipline, especially for improving the accuracy of tropical cyclone intensity forecasts. However, there is still room for more developments in this technology.

In a study that has recently been introduced and is very innovative, Meng et al. made TCP-NGBoost model, which is advanced and managed to merge the strong and competent sides of LightGBM and NGBoost algorithms. This model is a revolutionary tool in the field of tropical cyclone (TC) intensity forecasting considering the fact that it does not only quantify the uncertainty but also it vaults the traditional TC intensity forecasting in performance. Among all, the novelty of TCP-NGBoost demonstrates its great computational efficiency, leaving behind the resource-expensive techniques of super-ensemble models, and accomplishes view that competes with the current operational models to reach accuracy in forecasting with a 24-hour interval. TCP-NGBoost is undoubtedly able to make exceptional contribution to the treatment, yet on the perky side, the report addresses TCP-NGBoost struggles, which include its complex, non-linear relationships due to limited availability of the training data and the black box nature, in which understanding its internal mechanics is much complicated. Notwithstanding, however, TCP-NGBoost is an outstanding achievement contributing to the progress of risk assessment and decision-making through a refined and probabilistic approach to forecasting the intensity of the hurricanes, thus showing a path to winning this battle against such powerful and destructive forces of nature.

The research conducted by Tian and colleagues focuses on the creation of a 3 D Convolutional Neural Network model called 3DAttentionTCNet which incorporates the Convolutional Block Attention Module (CBAM) to estimate Tropical Cyclone intensity using satellite imagery channels. By utilizing infrared (IR) water vapor (WV) and microwave (PMW) channels the model enhances the accuracy of TC intensity prediction. The study highlights the effects of combining IR and PMW channels while also noting limitations when integrating WV channels, with IR ones. Through training and testing it was found that utilizing all three channels in a 3 D CNN with CBAM leads to the precise TC intensity estimation. The incorporation of CBAM into the network enhances feature recognition and channel selection related to TC intensity resulting in improved performance with a reduced error rate of 9.48 knots. Comparative assessments against existing models demonstrate that 3DAttentionTCNet surpasses approaches in satellite based TC estimation showcasing its competitiveness and potential for enhancing TC intensity prediction. This study emphasizes the efficacy of employing 3 D CNNs alongside attention mechanisms for processing multichannel satellite data, in disaster monitoring and response efforts.

III.Existing System

Cyclone intensity estimation has historically relied on several traditional methods, which have provided valuable insights into the strength of these powerful weather systems. These methods, though widely used, often exhibit limitations due to their subjective nature and dependence on visual interpretation.

A Saffir-Simpson Hurricane Wind Scale

The Saffir-Simpson Hurricane Wind Scale, developed in the early 1970s by engineer Herbert Saffir and meteorologist Robert Simpson, remains one of the most well-known and utilized methods for estimating cyclone intensity. This scale categorizes hurricanes based on sustained wind speeds, ranging from Category 1 (74-95 mph) to Category 5 (157 mph or higher). Each category is associated with specific potential damage impacts, providing a useful framework for emergency preparedness and public awareness.While the Saffir-Simpson scale offers a straightforward classification system, it has notable limitations. It focuses solely on wind speed and does not account for other factors contributing to cyclone intensity, such as storm surge, rainfall, or size. Additionally, the scale's threshold values are somewhat arbitrary and may not fully capture the complexity of cyclone impacts.

B Dvorak Technique

Developed by meteorologist Vernon Dvorak in the early 1970s, the Dvorak technique is a widely used method for estimating cyclone intensity based on satellite imagery interpretation. This technique relies on the visual appearance of cyclone cloud patterns, including the arrangement and temperature of cloud tops, to estimate the storm's intensity.The Dvorak technique employs a series of alphanumeric classifications, known as T-numbers, to assign a cyclone's intensity on a scale from T1.0 to T8.0. These classifications are based on various features observed in satellite imagery, such as the presence of an eye, the organization of cloud bands, and the curvature of convective cloud tops.While the Dvorak technique has been valuable in providing real-time intensity estimates, it is subject to interpretation bias and relies heavily on the skill and experience of the analyst. Additionally, the technique may struggle to accurately assess the intensity of rapidly evolving or asymmetric cyclones, leading to potential discrepancies in intensity estimates.

C Limitations of Traditional Methods

Despite their widespread use, traditional methods of cyclone intensity estimation suffer from several inherent limitations. Subjectivity and reliance on human interpretation introduce the potential for inconsistencies and errors in intensity assessments. Moreover, these methods often focus on specific aspects of cyclone behavior, such as wind speed or cloud morphology, while overlooking other critical factors influencing storm intensity, such as central pressure and environmental conditions.Furthermore, traditional methods may struggle to accurately capture the intensity of rapidly intensifying or weakening cyclones, leading to challenges in timely and reliable forecasts. As a result, there is a growing need for complementary approaches that integrate multiple data sources and utilize advanced technologies to improve the accuracy and reliability of cyclone intensity estimates.

IV.Proposed System

The whole purpose of this project is to create a technique or a method that can be used for cyclone intensity estimation as well as cyclone direction estimation with less time consumption and more accuracy as this is very sensitive and very important field in human lifes if there is any error in estimation sometimes it might lead to human life loss too, so accuracy is very important as well as time taken for estimation is also important here, if our method takes more time for estimation then the damage would already happen and even estimation of correct intensity would also be of no use, so here high accuracy and less time consumption both are very important so in order to reach the both needs we are using Deep Learning Technology more specifically we are using convolutional neural network for building our custom model. We are using convolutional neural network because we are working with image Dataset (i.e IR Images from INSAT-3D Satellite) as we know that convolutional neural network will be very useful while we are working with image dataset's and as we are building our custom model's here are building 2 different models one for Cyclone Intensity Estimation and Cyclone Directon Estimation .

Here in the proposed system, firstly we check whether there is any cyclone formation in the given image and if no then we dont perform any task but if there is any cyclone formation then we send that image to both Intensity and Direction Estimation models after that both models will give their outputs that is intensity estimation model will give Intensity value in Knots(i.e scale for measuring cyclone intensity like kilometers per hour in measuring speed of vehicle's) and direction estimation model will give the direction in which the model is moving .

A. Data extraction and data cleaning

Data extraction and cleaning play a critical role in cyclone intensity and direction estimation, as it directly impacts the accuracy of the model. The first step in the data extraction process is to obtain high-quality images of INSAT 3D Satellite. Once the images are obtained, the data-cleaning process begins. This process involves removing any irrelevant or noisy data from the dataset to ensure that the model only learns from meaningful patterns. This can include removing images with poor quality, incorrect labeling, or images that are too similar to others in the dataset. It is important to ensure that the dataset is balanced, with an equal number of images for each type of cyclones, to prevent bias in the model, In our project we have taken a preprocessed dataset so we need not perform this step again until we include some more images to the dataset, as we included some more images to the dataset so we followed this step.

The next step is to preprocess the images before feeding them into the model. This includes resizing the images to a uniform size, normalizing the pixel values, and converting the images to a format compatible with the model. Additional image augmentation techniques, such as rotation, flipping, or zooming, can also be used to increase the size of the dataset and improve the model's ability to generalize to new data, as images in the dataset will already be preprocessed before adding images to the dataset we need to perform all the preprocessing steps to images we are adding to the dataset.

In conclusion, data extraction and cleaning are crucial steps in the cyclone intensity estimation and cyclone direction detection process, as they directly impact the performance of the model. By obtaining high-quality images and carefully cleaning the dataset, we can ensure that the model learns only from relevant patterns and generalizes well to new data.

B. REGRESSION Using Convolutional Neural Networks

LAYER	DETAILS
Input Layer	Shape: (256, 256, 3)
Convolutional Layer 1	Filters: 256, Kernel Size: 3x3, Activation: ReLU, Padding: Same, Regularization: L1L2 (0.01), Batch Normalization, He Normal Initialization
Convolutional Layer 2	Filters: 256, Kernel Size: 3x3, Activation: ReLU, Padding: Same, Regularization: L1L2 (0.01), Batch Normalization, He Normal Initialization
Max Pooling	-
Convolutional Layer 3	Filters: 256, Kernel Size: 3x3, Activation: ReLU, Padding: Same, Regularization: L1L2 (0.01), Batch Normalization, He Normal Initialization
Convolutional Layer 4	Filters: 128, Kernel Size: 3x3, Activation: ReLU, Padding: Same, Regularization: L1L2 (0.01), Batch Normalization, He Normal Initialization
Max Pooling	-
Convolutional Layer 5	Filters: 128, Kernel Size: 3x3, Activation: ReLU, Padding: Same, Regularization: L1L2 (0.01), Batch Normalization, He Normal Initialization
Convolutional Layer 6	Filters: 64, Kernel Size: 3x3, Activation: ReLU, Padding: Same, Regularization: L1L2 (0.01), Batch Normalization, He Normal Initialization
Max Pooling	-
Convolutional Layer 7	Filters: 64, Kernel Size: 3x3, Activation: ReLU, Padding: Same

Table 1: Table of details about each layer of CNN Model

Layer (type)	Output Shape	Parameters
input_1 (Input Layer)	(None, 256, 256, 3)	0
conv2d (Conv2D)	(None, 256, 256, 256)	7168
Batch Normalization (Batch Normalization)	(None, 256, 256, 256)	1024
tf.nn.relu(TFOpLambda)	(None, 256, 256, 256)	0
conv2d_1 (Conv2D)	(None, 256, 256, 256)	590080
batch_normalization_1 (Batch Normalization)	(None, 256, 256, 256)	1024
tf.nn.relu_1 (TFOpLambda)	(None, 256, 256, 256)	0
max_pooling2d (MaxPooling2 D)	(None, 128, 128, 256)	0
Flatten layer	(None,4096)	0
Output Layer(Dense Layer)	(None,1)	0

Total parameters : 1778961 **Trainable parameters : 1776497** **Non-trainable parameters: 2464**

Table 2: Table of CNN Layers Output Shape and Number of Parameters

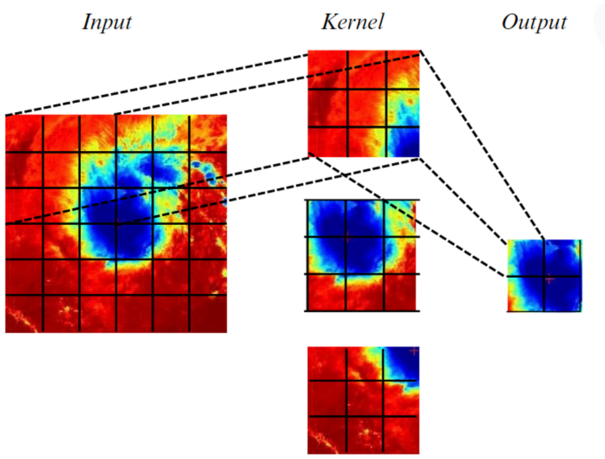

Figure 1: Convolutional Layer

a. Convolutional Layer

Convolutional layers are pivotal elements in the Deep Learning.Initially the image was divided into a 2x2 matrix holding their RGB, length, and width in each cell.The Conv2D are the 2 dimensional convolutional layers which performs mapping of the input image.The kernel plays a key role in filtration of the image through iterations of the every cell emerged in the matrix.These Conv2D layers will filter the input IR image of the cyclone and computes the dot product of the image positions to extract the patterns.These patterns are helpful to classify the IR images of the cyclones for feature mapping.The input IR image is normalized to increase the data gain by rescaling and recentering of the image data called Batch Normalization.

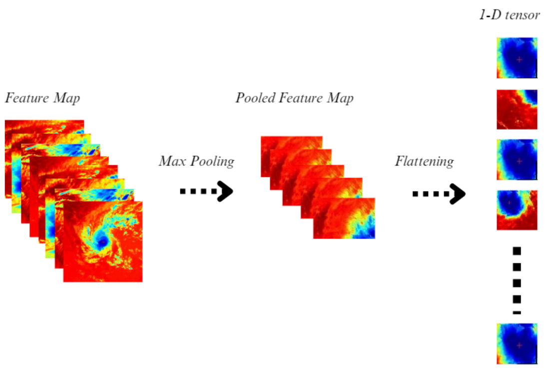

Figure 2: pooling layer and Flatten Layers

b.Pooling Layer

Pooling is the process of data reduction where the blocks of the image with maximum or average features are merged into a single block through certain operations.These blocks will enrich the features by collecting the cyclone eyewall patterns of the IR image where the detection and processing time will be reduced.The flatten layers will convert the multi dimensional tensor generated from the pooling layers to a one-dimensional tensor.

c.Activation function

Rectified Linear Unit (ReLU) is the prominent activation function situated at the dense layers of the Neural network which will results the maximum for the positive and zero for all the negative. ReLU is the most effective activation function connected to the output of the flatten layers and results the output to the fully connected layers.ReLU exhibits the Non-linearity property and resolves the vanishing gradient issue compared to other variants.

d.Fully connected layers

Every neuron carries out a linear transformation on the input vector using a weights matrix. This setup guarantees the establishment of all potential connections between layers, signifying that each element in the input vector directly impacts every element in the output vector.

C. User interface

Simplicity and accessibility are priorities in the design of StromSight's user interface. Due to it's user-friendly nature people with little to no experience in computer science can use it. The interface enables users to quickly test the application and all of its features without needing in-depth technical knowledge.
Images of cyclone that the user wants to be estimate it's intensity and direction of cyclone can be uploaded to the system through StromSight's Interface. Next, using the Convolutional Neural Network (CNN) architecture—the interface swiftly analyzes the submitted photos. This CNN variant has been taught to accurately estimate the intensity and direction of cyclone.
After the analysis is finished, the user is provided with intensity value of IR image of cyclone uploaded in Knots along with direction ie either north direction or south direction or east direction or west direction .

V.Working

Two essential components for cyclone analysis are included in the project: a direction prediction model and an intensity estimating model. Convolutional neural networks (CNNs), a deep learning technology, are used by these models to process INSAT-3D IR pictures and produce insightful information.

The intensity estimation algorithm analyzes infrared images using a CNN architecture that was trained on a collection of photographs taken during cyclones. It gains the ability to recognize characteristics, including cloud structure and temperature, that are indicative of cyclone strength levels. The model uses parameter optimization approaches, such as the Adam optimizer and mean squared error (MSE) loss, to reduce errors in its predictions and improve accuracy. In order to avoid overfitting and guarantee the model's flexibility to various cyclone conditions.

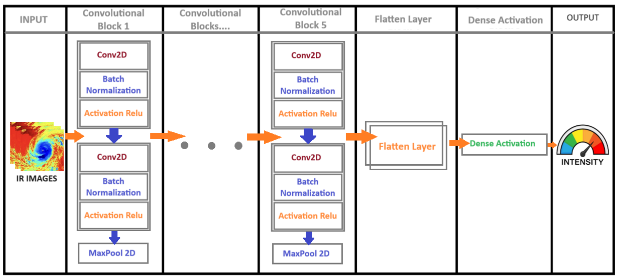

Figure 3:Flow of Images through Multiple Layers

Similar to this, the direction prediction model uses a CNN architecture to analyze infrared images in order to forecast the direction of cyclone movement. It becomes capable of recognizing spatial patterns in the images that link to different directions of motion, such as spinning cloud formations. By using techniques like categorical cross-entropy loss and optimization with the Adam optimizer to divide cyclone tracks into cardinal directions, the model enhances its forecasts.

By incorporating these models into the Streamlit-created user interface, we have increased user accessibility. This smooth link allows users to upload infrared photos of cyclones and obtain instantaneous, real-time forecasts about the movement's direction and strength. Because of the accuracy, dependability, and user-friendliness of the interface, users are equipped with the knowledge and resources they need to effectively prepare for and minimize future disasters.

Comprehensive evaluations are carried out with independent test datasets in order to validate the models' performance. This guarantees the models' ability to forecast cyclone parameters with accuracy and shows their promise for cyclone analysis jobs in the actual world.

VI. Results & discussion

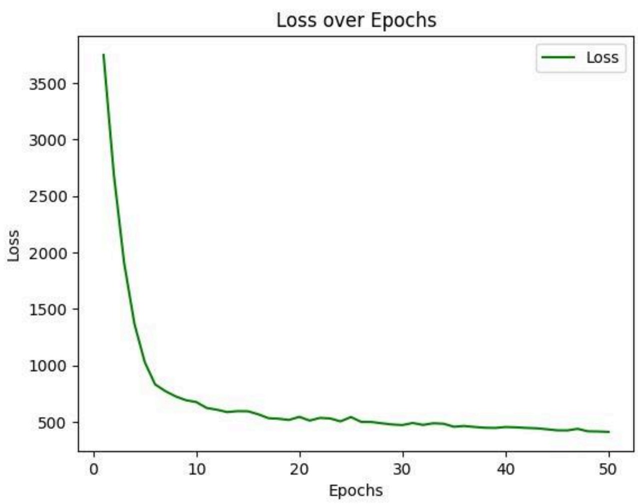

Figure 4: Graph of Loss over Epochs

The above graph describes the losses occurred for every epoch performed by the model.Initially the loss of the model is very high because it was not totally trained with the images.The MSE of the model for the first epoch is 3623.62. We have performed 50 epochs to train the model with various IR images of the cyclones with different intensities. The model has trained itself with every epoch and reduces the loss percentage and increases the accuracy . As per the graph we can notice that there was a vast difference in the detection of the cyclone intensity for first 10 epochs.

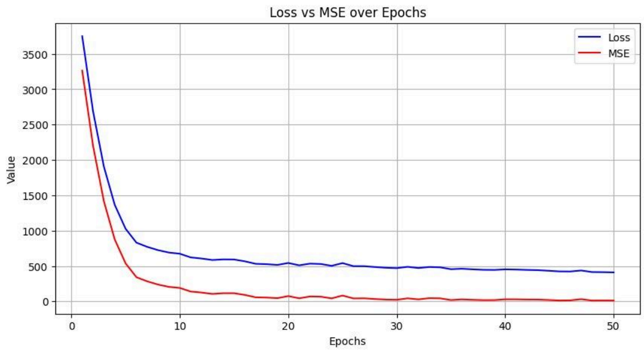

Figure 5: Graph of Loss VS MSE

The above graph describes the losses occurred in comparison to Mean Square Error over total 50 Epochs on which the model is trained initially the MSE value at first epoch was 3263.6118 and the loss value is 3749.2905 gradually it came down i.e loss is loss: 410.2502 and MSE is 12.4838 which is very huge change and increase in the accuracy of the model

VII. Conclusion

The Cyclone Intensity Estimation module achieved impressive performance with a RSME of 3.53 and an accuracy score of 87%. This signifies that the model's predictions closely matched the actual labels, indicating robust learning and prediction capabilities. The low RSME value suggests that the model effectively minimized errors during the training process , we have reduced the loss value to 410.2502 and by performing good training we were able to reduce the Mean Square Error of the model to 12.4838

VIII. Future scope

While working on getting intensity and direction of cyclones, we should also significantly improve our system capable of predicting what losses could be expected as a result. It implies the determination of valuable parameters, such as where exactly the cyclone will come closer to the landand hit. We also have to take into account the number of people who live in those areas, so we are able to understand the human effects. Furthermore, we need to include sectors within, such as factories and industries since they could be damaged too. Also, there is a need to evaluate each farmland to know farmers' livelihoods could be affected. The comprehensive approach we are taking would be to paint a vivid picture of a cyclone's destructive power, this way we can think of proactive steps to take in order to get prepared and to be able to respond adequately. Upon conditioning the storm surge and wind speeds into our estimation process, we will be able to utilize our resources better and plan evacuations earlier, thus saving the coastal population from the cyclone's impact.

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